Proposal of local feature vector focusing on the differences among neighboring ROI's.

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It is difficult to cope with the product surface inspections with complicated textures by using the conventional procedures such as basic banalization, morphology processing, etc. Then we propose a set of new local features which could be sensitive to the differences among neighboring ROI's and experimented successfully how the proposed features were effective.

Visual inspection ; Metal surface ; PCB ; Machine Learning

I. INTRODUCTION

In previous method [1], the image is divided by blocks with respect to the image using the LBP feature and their mean, median, kurtosis, and energy are calculated and judged as defects when exceeding the non-maximum suppression threshold It was. However, although this approach is fast, since the classification performance is on average about 93%, the visual inspection approach is incomplete. We are trying at versatile visual inspection. We propose a new local feature which were sensitive to the differences among neighboring ROI's and experimented successfully how the proposed features were effective.

II. CONVENTIONAL PROBLEMS

DNN (Deep Convolution Neural Network) [2] [3] is an approach to externally inspected with versatility. In recent years, DNN has received attention as a general object recognition algorithm and has been applied to appearance inspection. If many master images of defect are able to train, it is possible to feature extraction and classification from input image. However, as a general problem of DNN, the feature extraction of DNN is black boxed, and I do not know why the result is obtained. Then, the discrimination result is strongly influenced by the learning data, and the feature amount varies depending on the learning data set, which is difficult to handle when introducing the apparatus. J. Masci et al [4] were trying to defect detection by using learned defect ROI image and DNN, error rate was about 10% and clarified about the difficulty of solving the visual inspection problem with DNN. Therefore, applying the general object recognition algorithm to visual inspection does not succeed, it seems that it will be necessary to prepare some input image in visual inspection as knowledge. In this paper, we propose local feature vectors focused on [feature of skin state] in Chapter 4, and verify the effectiveness of the proposed method by show classification results feature vectors with machine learning (DNN and SVM).

III. PROPOSED METHOD

Visual inspection can be put into the following two processes.

(1) Comparison of inspection region with surface neighborrhoo -ds.

(2) Comparison of products in temporal patterns.

(3) Relative map generation.

In the proposed inspection method, we propose feature vector for (1) in Chapter 4, explain the classification for (2) between "Defect region" and "Normal region" by using machine learning in Chapter 7. That is, we propose an appearance inspection method combining (1) and (2).

IV. PROPOSAL OF LOCAL FEATURE VECTOR

The proposed feature vector presents how much the local region differs from other regions from a inspect region as features. The local feature vector that focuses on the suggested proposed feature vector is a value secondarily calculated based on feature values such as brightness value, gradient strength, gradient direction, HOG feature, LBP feature. In this paper, we conducted the experiment using the gradient strength as the most basic method.

The calculation of the proposed method is shown in Figure 1, which consists of the following three steps.

(1) Block division of image.

(2) Inner products of pairs of local feature histogram vectors.

(3) Relative map generation.

V. LOCAL AREA FEATURE INTER-HISTOGRAM DOT PRODUCT.

In the calculation of the proposed method, a histogram of the feature of interest in each block is used as a feature. This is called a local feature histogram. The feature of interest is luminance, gradient strength, HOG [5], LBP [6]. Generally, the luminance value of a digital image is 256 levels, it can be used

978-1-5386-2615-3/18/$31.00 ©2018 IEEE

as a histogram of a class number 256, and other features also applied the same levels. Specifically, in case of gradient strength, the values of gradient strength become approximately 3000 kinds due to the nature of the Sobel filter. Thus, the values of gradient strength is normalized to generate a local histogram of 256 levels. The number voted on the local histogram is determined by the block size. The number of classes in the histogram was experimentally obtained, and in this paper the proposed method was calculated with the number of classes of the histogram being about 5. When considering the frequency of one class of the histogram as one feature, it is one point in the feature space of the same dimension number as the number of classes of the histogram and can be regarded as a feature vector. The inner product of the feature histogram of the block of interest is obtained by (1). Thereafter, the inner product of 4 neighborhoods is added with the obtained inner product overlapping the left and right upper and lower half blocks. By this processing, the target block holds the surrounding texture region.

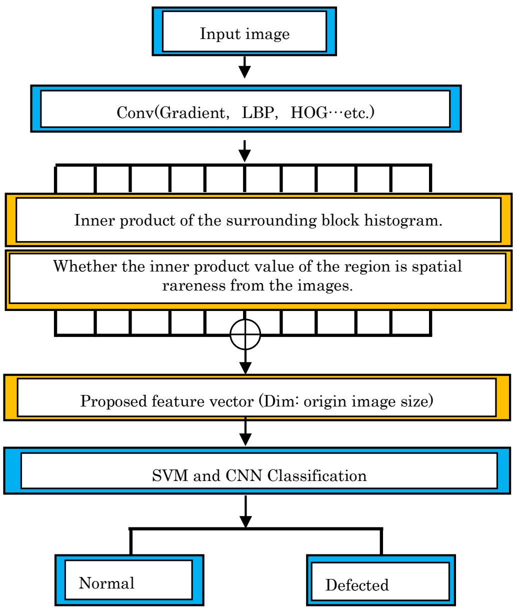

Fig. 1. Proposed method algorithm flow.

$$R(u,v)=\sum_{u=0}^{U-u-1}\sum_{v=0}^{V-v-1}\left(\frac{H(u,v)\cdot h(u,v)}{|H(u,v)|\cdot|h(u,v)|}\right) \quad (1)$$

VI. RELATIVE MAP GENERATION

First, the inner product H (u, v) of all the blocks are sorted and the result is set as a list L (z) (z = 0, 1, 2 ... (U - 1) (V- 1)). Then, as shown in equation (2), calculate the median of L (z), and find the distance R (u, v) from the median. As a result, it is possible to calculate how far the inner product is relatively distant from the other blocks compared with other blocks.

$$R(u,v)=\sum_{u=0}^{U-u-1}\sum_{v=0}^{V-v-1}|\left(H(u,v)\right)-median\{\mathrm{L(z)}\}| \quad (2)$$

Next, the block size is changed from 20 pixels to 30 pixels, and the relative map discretized from 0 to 255 is restored to the original image size and added.

VII. EXPERIMENTAL DATA AND PROPOSED METHOD IMAGE

Examples of strongly textured surfaces and experimental results of the proposed method are shown in Figure 2. The examples are from an artificial dataset provided by the DAGM (German Association for Pattern Recognition) and Robert Bosch GmbH and represent different kinds of defects on varying background texture [7]. Table 2 shows the results of classification by CNN using 1150 positive samples and 150 negative samples applying the proposed method. And classification performance exceeded that of comparison method.

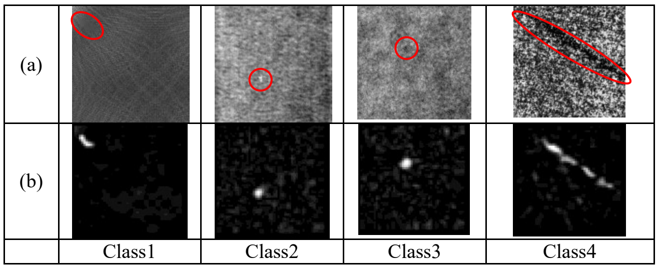

Fig. 2. Experimental results of the proposed method for all defect classes

TABLE I. SVM CLASSIFICATION

ClassNo/Accuracy	Origin Dim: 512*512	Hog Dim 60	Lbp Dim: 512*512)	Proposed method Dim: 512*512
Class1	48%	48.66%	58.66%	99.33%
Class2	52.66%	50.66%	54.66%	100%
Class3	51.33%	50.66%	56%	98.66%
Class4	66.665	55.33%	55.33%	99.63%

TABLE II. DNN CLASSIFICATION

ClassNo/Accuracy	Origin Dim: 512*512	Hog Dim 60	Lbp Dim: 512*512)	Proposed method Dim: 512*512
Class1	52.5%	56.25%	51.24%	100%
Class2	80.65%	48.12%	50%	100%
Class3	95.62%	56.25%	51.24%	49.38%
Class4	85.62%	50%	53.13%	98.75%

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